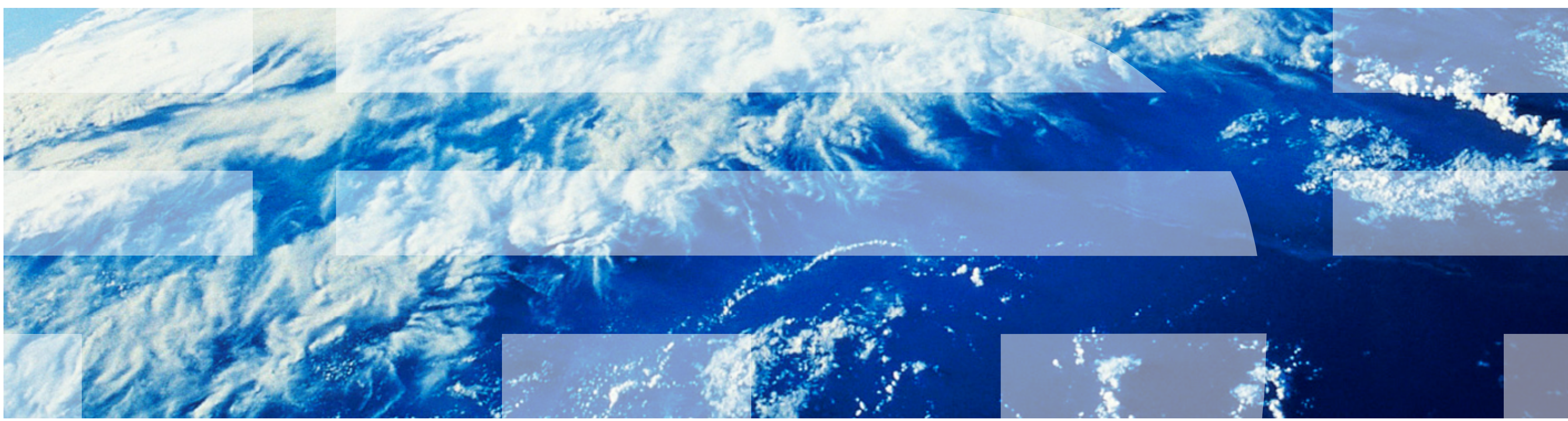
Computer Systems for Data Science
Topic 4

Memory/Storage Hierarchy

Database and Key-value Store Architecture



What we'll cover

- **Memory and storage hierarchy and trade offs**
  - **DRAM**
  - **Flash**
  - **Disk**
  - **NVM**
- **Indexing**
- **Bloom filters**
- **Key-value stores**
  - **RocksDB**
- **Database on top of key-value store**
  - **MyRocks**

Tasks of the database

- Low level tasks:
  - Store the tables
    - Example: How do I physically store the tables on disk?
  - Read/insert/delete/update data
    - Example: What is the entry of cuid 1212?
- Higher level semantics:
  - Logging
  - Concurrency control
    - Example: what’s the best schedule to execute a set of transactions?
  - Query optimization
    - Example: should I first do the projection, or the aggregation?

We'll focus on the systems aspects of some of these questions

- Low level tasks:
  - **Store the tables**
    - Example: How do I physically store the tables on disk?
  - **Read/insert/delete/update data**
    - Example: What is the entry of cuid 1212?
- Higher level semantics:
  - **Logging**
  - Concurrency control
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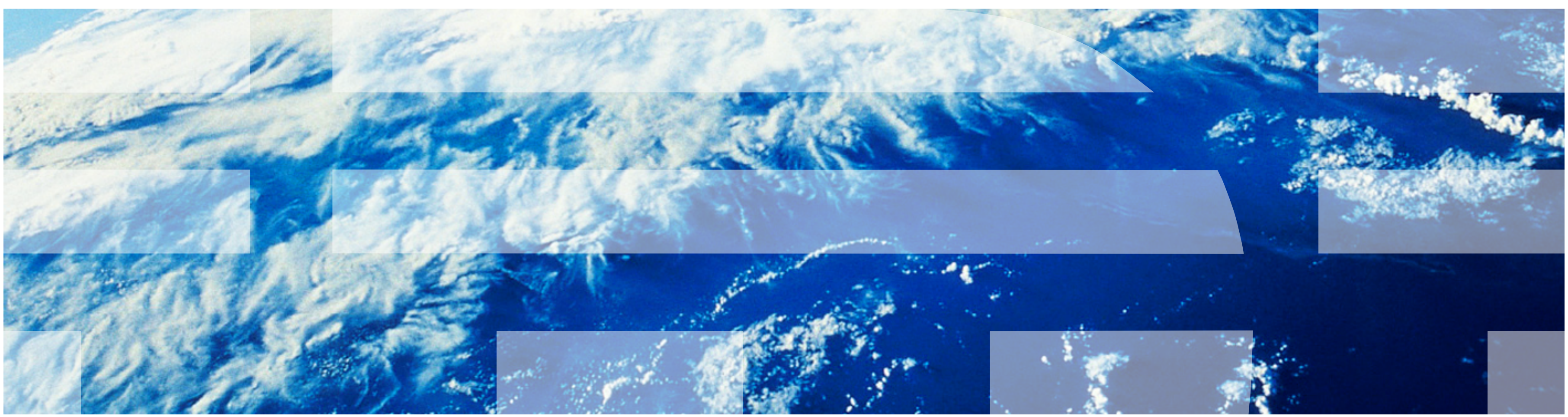
Borrowed/adapted from Greg Ganger

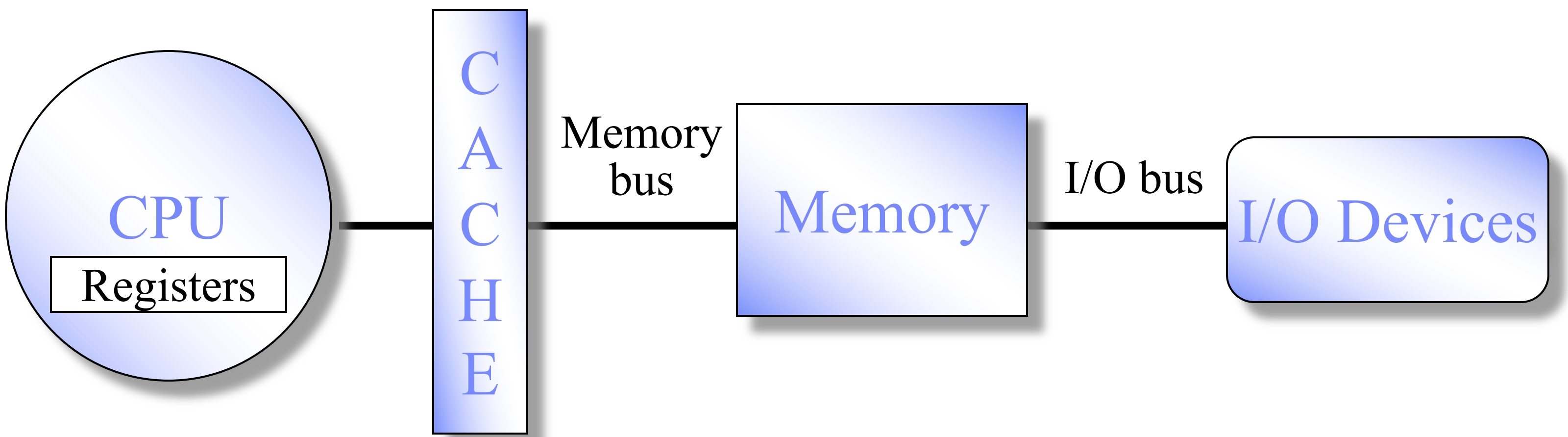
Memory and Storage Hierarchy



The memory hierarchy

- Memory and storage present several trade-offs:
  - Cost
  - Latency and throughput
  - Durability/volatility (is information lost when power goes down?)
  - Access granularity
- Can't have it all!

The memory hierarchy



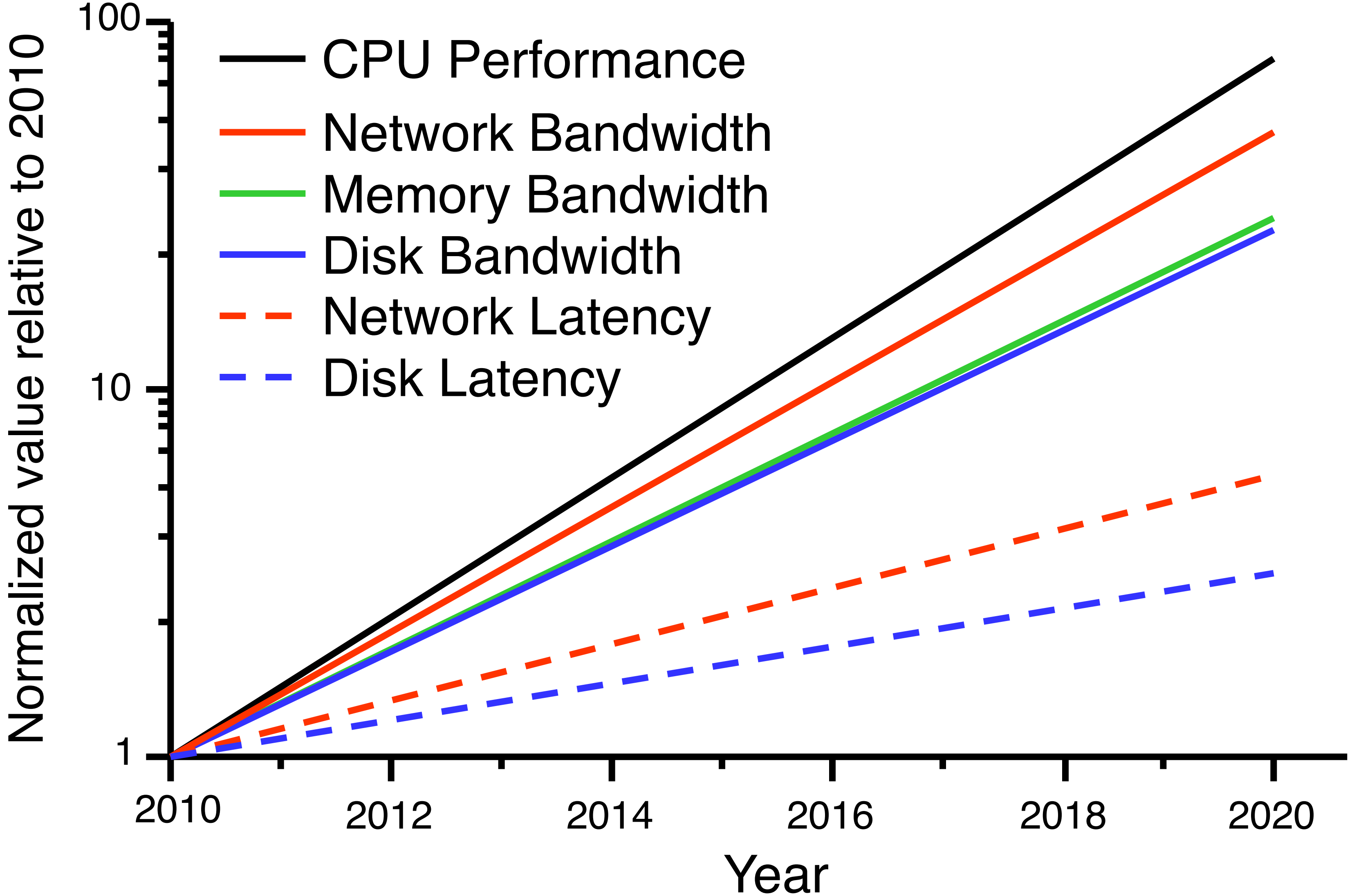
	Register Reference	L1/L2/L3 Cache Reference	Memory Reference	Disk Reference
Size:	300 B	20 / 1 / 4 MB	8-128 GB	1-3 TB
Speed:	0.2 ns	1 / 5 ns	25-100 ns	5-10 ms (smaller, faster for Flash SSD)

Trade-offs (rough numbers)

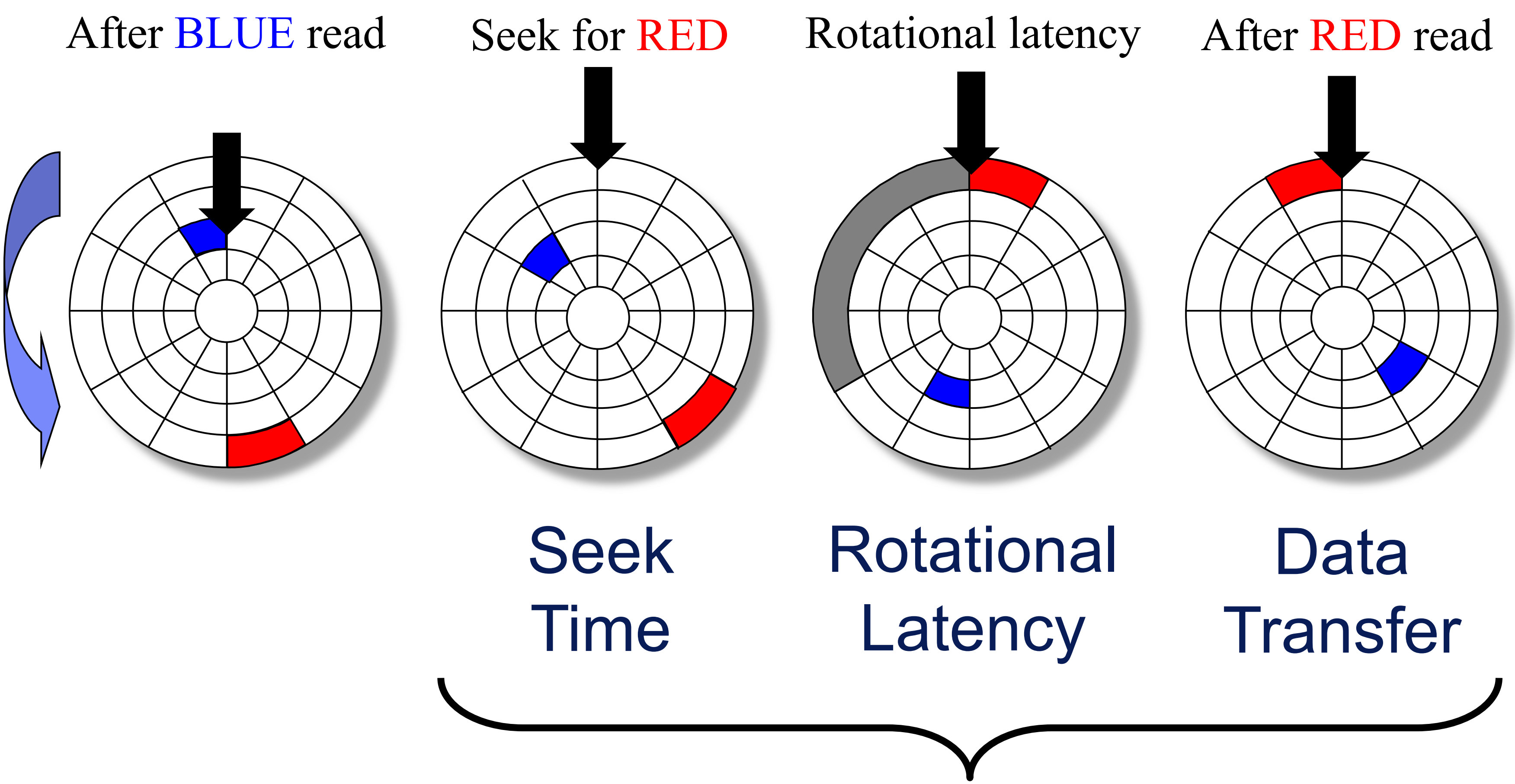
	Memory (RAM)	Flash	Magnetic Disk
Cost/GB	$3	$0.1	$0.04
Latency, random read	25-100ns	50-100us (1000X RAM)	5-10ms (100X Flash)
Bandwidth, sequential reads	10GB/s	250MB/s	150MB/s
Durable?	No	Yes	Yes
Effective access granularity	Byte reads and writes	4KB read MBs write	MBs read and write

Sources:
https://jcmit.net/memoryprice.htm,
https://www.amazon.com/Intel-660p-1-0TB-80mm-978350/dp/B07GCL6BR4
https://www.amazon.com/Seagate-Portable-External-Hard-Drive/dp/B07CRG7BBH/ref=sr_1_3?keywords=hard+disk+1tb&qid=1579102708&sr=8-3

Technology Trends



HDD / Magnetic Disk

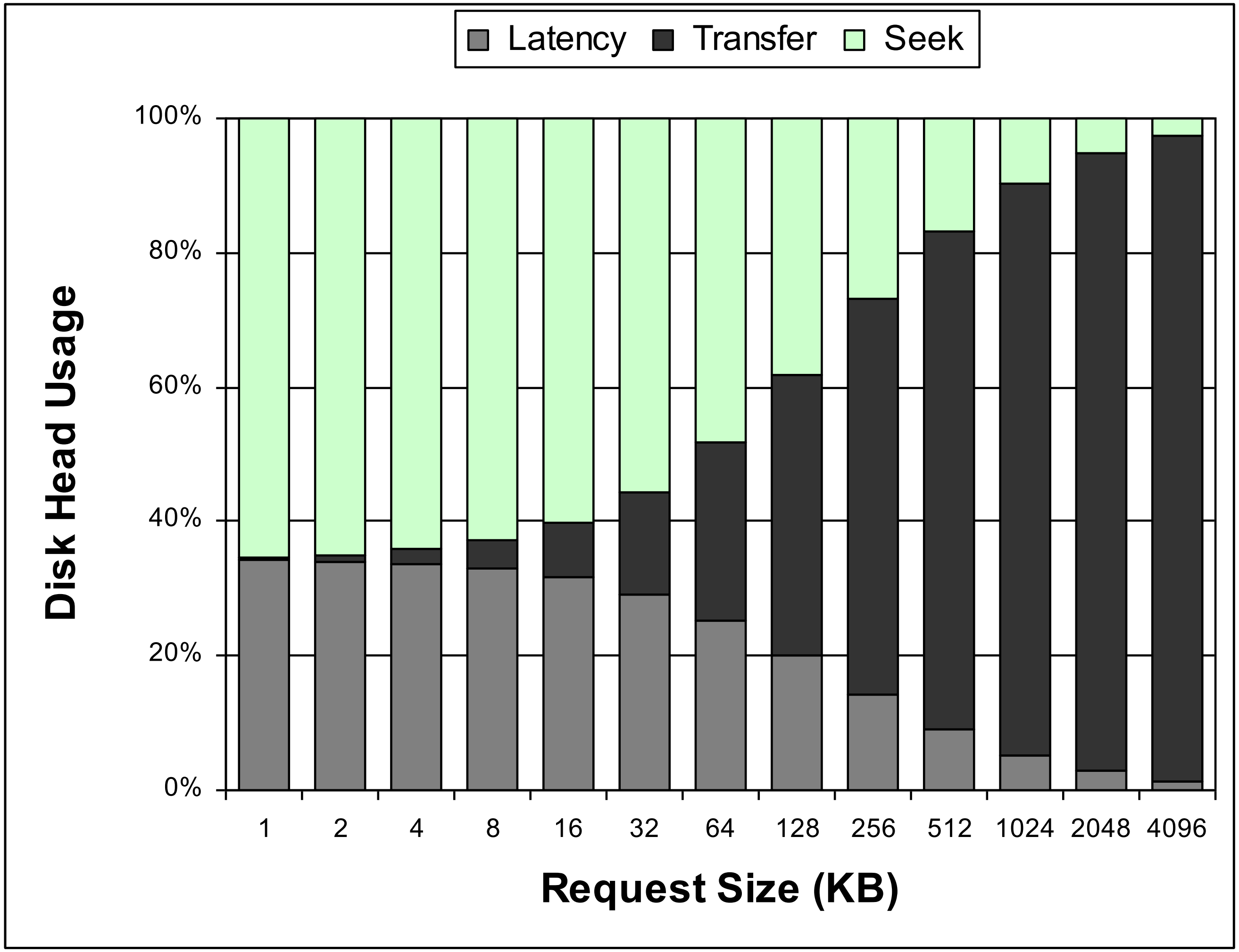


Access Time = seek time + rotation time
+ data transfer time
(for RED)

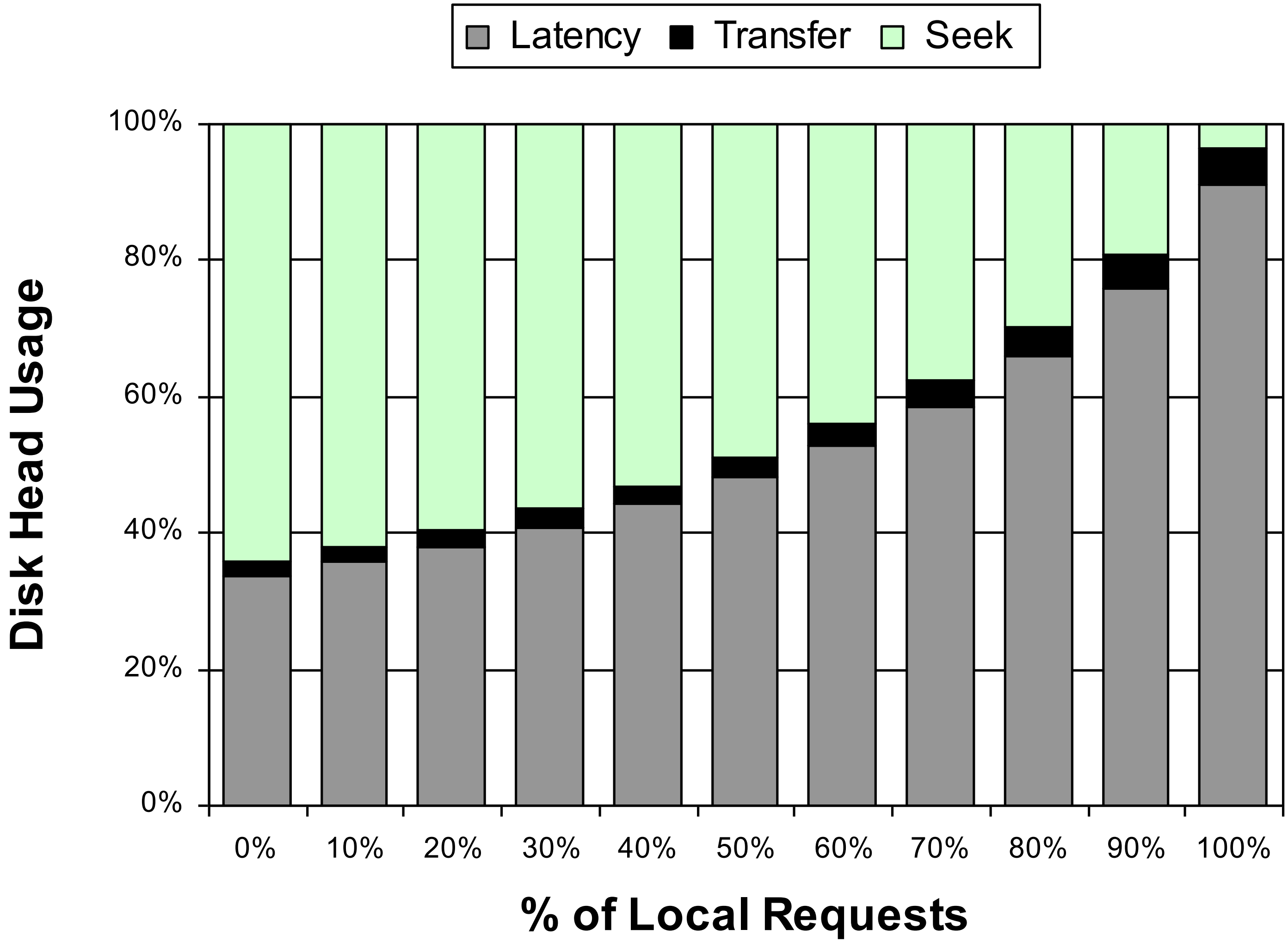
Modern HDD performance

- Seek times: 1 – 6 ms, depending on distance
  - Average 2 – 4 ms
  - Not necessarily improving
    - It's a mechanical part!
- Rotation speeds: 4,200 – 15,000 RPM
  - Average latency of 2-12 ms
  - Typically slowing down
    - But also mechanical
- Data rates: 60-125 MB/s*, depending on zone
  - avg sector transfer time of 25 us
  - improving at 0-20+% per year

HDD utilization (random requests)



Locality is important (4KB requests)



Flash

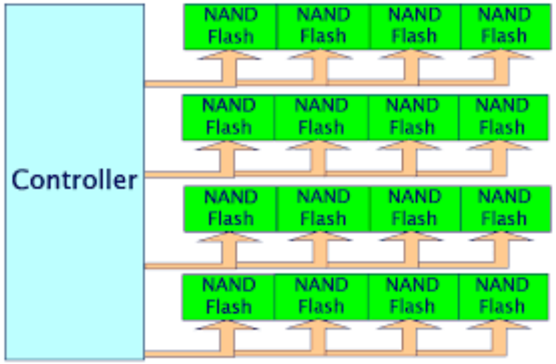
- Solid-state storage technology
  - Non-volatile memory chips, disk interface, **no mechanical moving parts (yay!)**
  - Fast access (no seeks) but more costly than mechanical disks
  - Lower power (~none if not accessing), noise free (laptops!)
- Performance differences
  - No seeks means high rates of small random access
- Reliability differences
  - Device fatigue (eventually stops being programmable)
  - Device retention (information leaks away)

Flash performance is very different than magnetic disk

- Small random reads (no moving parts)
  - much, much lower average latency than mechanical disks
    - e.g., 10s of microseconds
  - orders of magnitude higher throughput than mechanical disks
    - e.g., 10s to 100s of 1000s of operations per second
- Write performance is more complicated
  - Small writes usually 100s of microseconds
    - Need to erase and reprogram flash cells → much longer time than reads
  - Write throughput more lower than reads for small objects
  - Need to write in large contiguous chunks (tens-hundreds of MBs) to get good performance

Flash prefers large sequential writes

- Large sequential writes perform better on flash. Why?
- **Reason 1:** Erase granularity != write granularity
  - In order to write new data to flash, data needs to be erased first
  - Erasures are done in a block granularity:
    - Block is 4-16KB
  - Writing even 1 bit requires rewriting 4-16KB!
- **Reason 2:** Flash uses multiple channels to get high throughput
  - Writes are *multiplexed* across multiple chips in parallel for high throughput
  - A single logical written block gets chopped up into many physical blocks



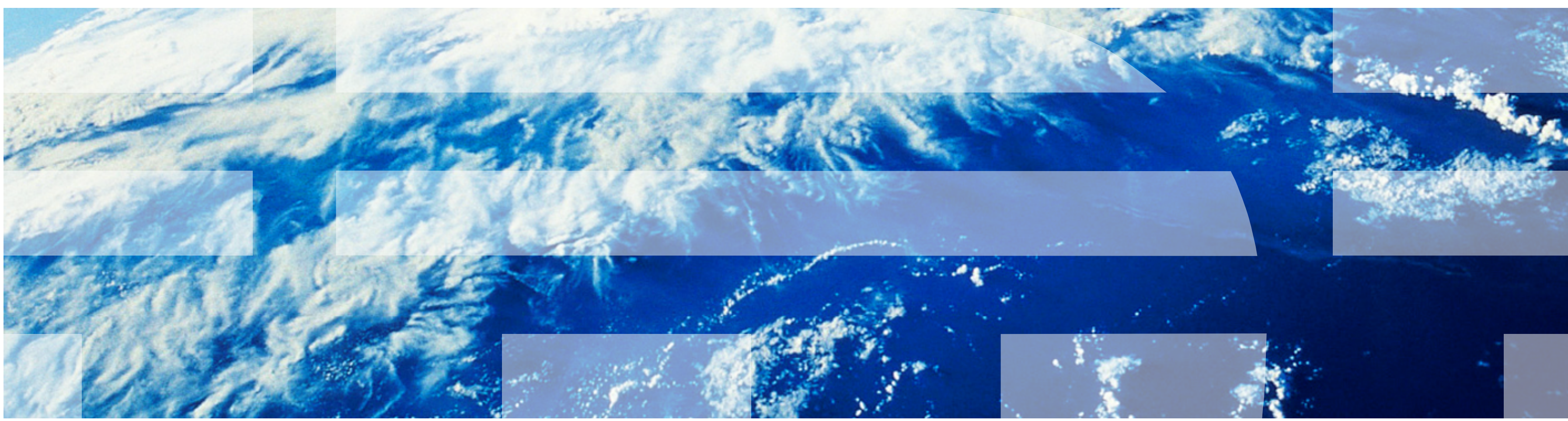
For optimal performance: writes typically need to be > 8MB!

Wear leveling: spread writing evenly in SSD

- Each flash cell can only survive a given number of writes
  - 500 (USB stick), 3,000-100,000 (SSD drives)
- Each block wears independently, so a heavily written block can wear out long before a mostly-read block
  - *Wear leveling* is remapping of addresses to better balance the number of write cycles seen by each block
  - This is done transparently by the storage device, but can lead to unexpected performance drops

Adapted from Database System Concepts, 7th edition, Silberschatz, Korth and Sudarshan

Indexing



Indexing

- Indexing mechanisms used to speed up access to desired data.
  - E.g., author catalog in library
- **Search Key** - attribute to set of attributes used to look up records in a file.
- An **index** consists of records (called **index entries**) of the form

search-key	pointer

- The index is typically much smaller than the original data
  - E.g., 100X smaller
- Where would you store the index?
  - Usually in memory
  - → Index has to be small, since memory capacity is limited

Index Evaluation Metrics

- Access types supported efficiently:
  - Records with a specified value in the attribute
  - Records with an attribute value falling in a specified range of values
- Access time
- Insertion time
- Deletion time
- Space overhead

Ordered Indices

- In an **ordered index,** index entries are stored sorted on the search key value.
- **Primary index:** in a sequentially ordered file, the index whose search key specifies the sequential order of the file.
  - The search key of a primary index is usually but not necessarily the primary key.
- **Secondary index**: an index whose search key specifies an order different from the sequential order of the file.

Dense Index Files

- **Dense index** — Index record appears for every search-key value in the database.
- E.g. index on *ID* attribute of *instructor* relation

10101	
12121	
15151	
22222	
32343	
33456	
45565	
58583	
76543	
76766	
83821	
98345	

10101	Srinivasan	Comp. Sci.	65000	
12121	Wu	Finance	90000	
15151	Mozart	Music	40000	
22222	Einstein	Physics	95000	
32343	El Said	History	60000	
33456	Gold	Physics	87000	
45565	Katz	Comp. Sci.	75000	
58583	Califieri	History	62000	
76543	Singh	Finance	80000	
76766	Crick	Biology	72000	
83821	Brandt	Comp. Sci.	92000	
98345	Kim	Elec. Eng.	80000	

Dense Index Files (Cont.)

- Dense index on *dept_name*, with *instructor* file sorted on *dept_name*

Biology	
Comp. Sci.	
Elec. Eng.	
Finance	
History	
Music	
Physics	

76766	Crick	Biology	72000	
10101	Srinivasan	Comp. Sci.	65000	
45565	Katz	Comp. Sci.	75000	
83821	Brandt	Comp. Sci.	92000	
98345	Kim	Elec. Eng.	80000	
12121	Wu	Finance	90000	
76543	Singh	Finance	80000	
32343	El Said	History	60000	
58583	Califieri	History	62000	
15151	Mozart	Music	40000	
22222	Einstein	Physics	95000	
33465	Gold	Physics	87000	

Sparse Index Files

- **Sparse Index**: contains index records for only some search-key values.
  - Applicable when records are sequentially ordered on search-key
- To locate a record with search-key value *K* we:
  - Find index record with largest search-key value < *K*
  - Search file sequentially starting at the record to which the index record points

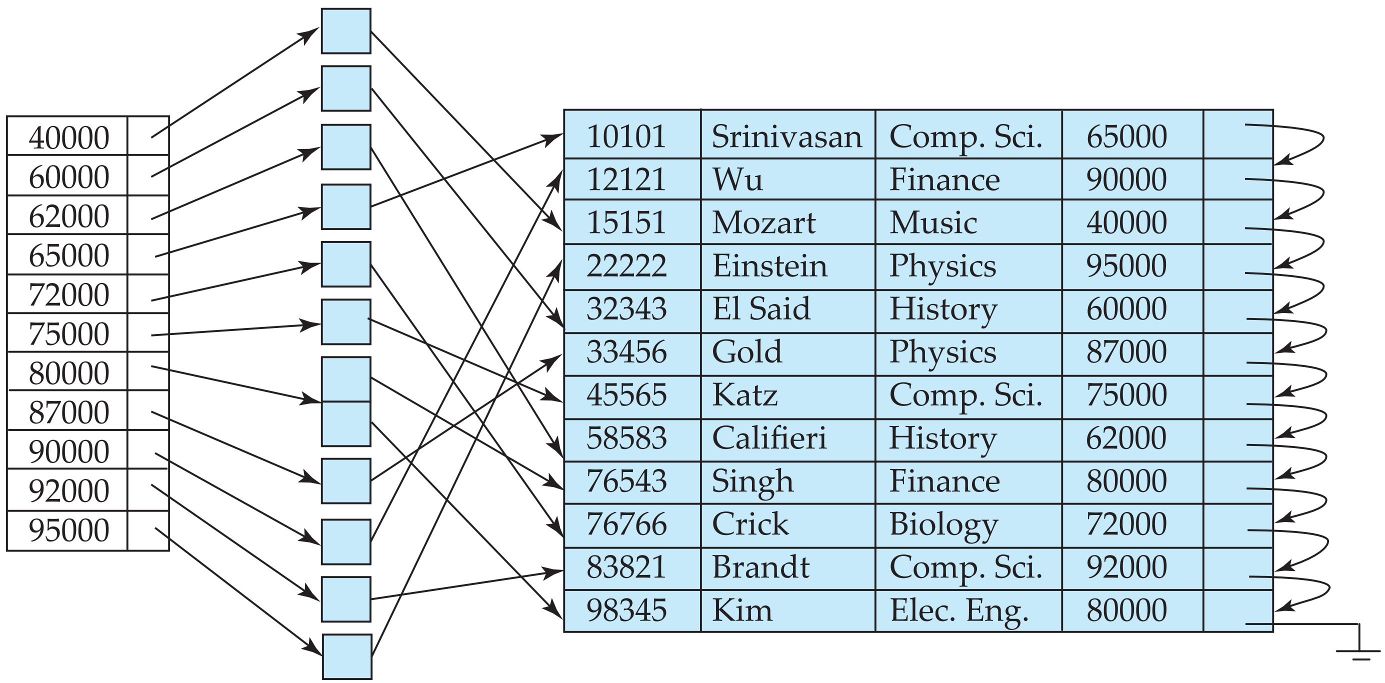
10101	
32343	
76766	

10101	Srinivasan	Comp. Sci.	65000	
12121	Wu	Finance	90000	
15151	Mozart	Music	40000	
22222	Einstein	Physics	95000	
32343	El Said	History	60000	
33456	Gold	Physics	87000	
45565	Katz	Comp. Sci.	75000	
58583	Califieri	History	62000	
76543	Singh	Finance	80000	
76766	Crick	Biology	72000	
83821	Brandt	Comp. Sci.	92000	
98345	Kim	Elec. Eng.	80000	

- Compared to dense indices:
  - Less space and less maintenance overhead for insertions and deletions
  - Generally slower than dense index for locating records

Secondary Index Example

- Secondary index on salary field of instructor

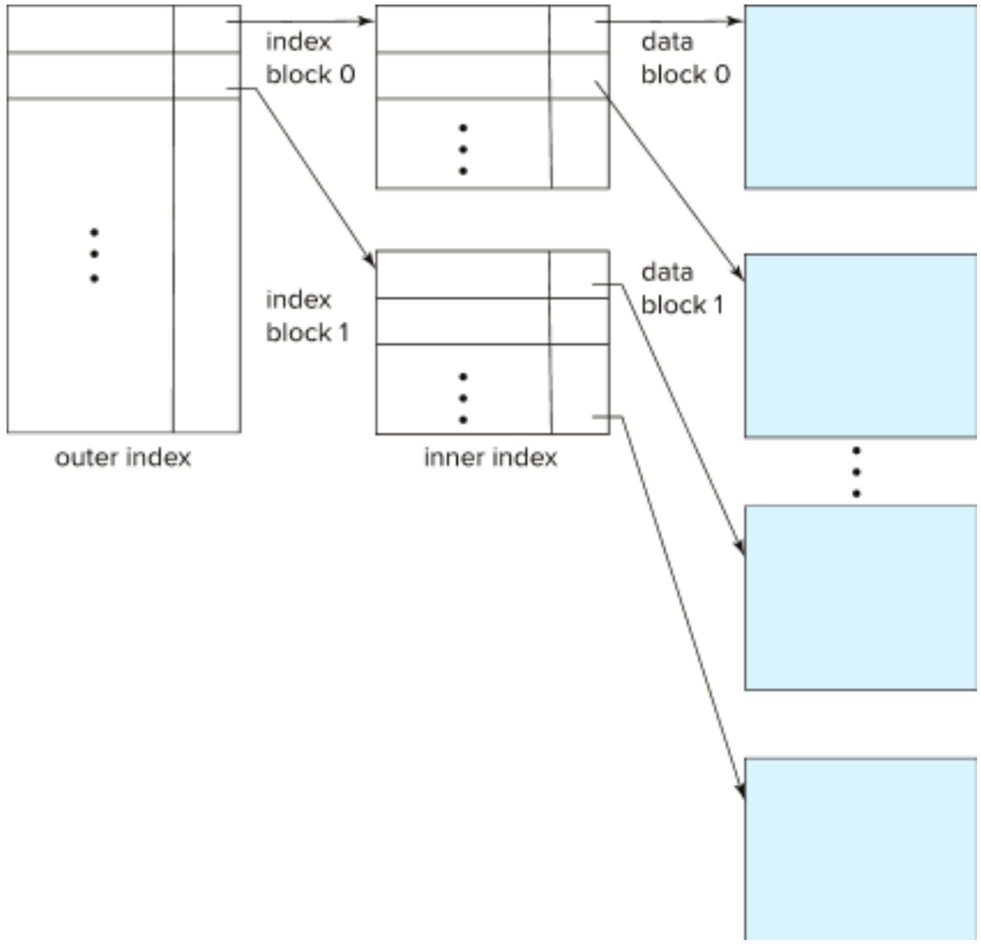


- Index record points to a bucket that contains pointers to all the actual records with that particular search-key value.
- Secondary indices have to be dense
  - Why?

Multilevel Index

- If index does not fit in memory, access becomes expensive.
- Solution: treat index kept on disk as a sequential file and construct a sparse index on it.
  - outer index – a sparse index of the basic index
  - inner index – the basic index file
- If even outer index is too large to fit in main memory, yet another level of index can be created, and so on.
- Indices at all levels must be updated on insertion or deletion from the file.
- File systems often use a multilevel index (e.g., nested directories)

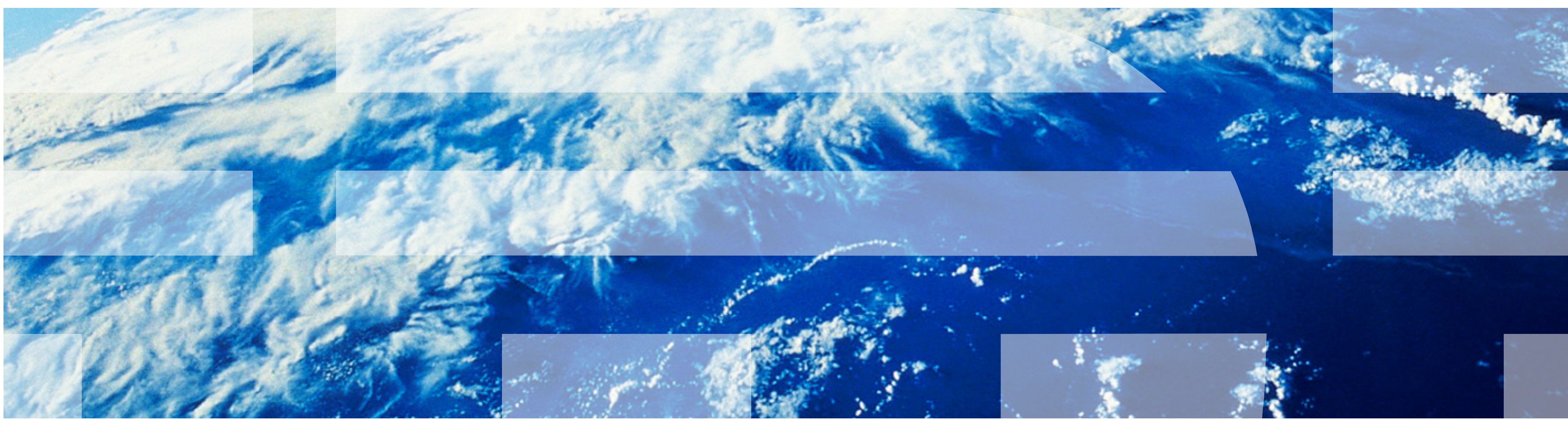
Multilevel Index (Cont.)



Index Update: Insertion

- **Single-level index insertion:**
  - Perform a lookup using the search-key value of the record to be inserted.
  - **Dense indices** – if the search-key value does not appear in the index, insert it
    - Indices are maintained as sequential files
    - Need to create space for new entry, overflow blocks may be required
  - **Sparse indices** – if index stores an entry for each block of the file, no change needs to be made to the index unless a new block is created.
    - If a new block is created, the first search-key value appearing in the new block is inserted into the index.
- **Multilevel insertion and deletion:** algorithms are simple extensions of the single-level algorithms

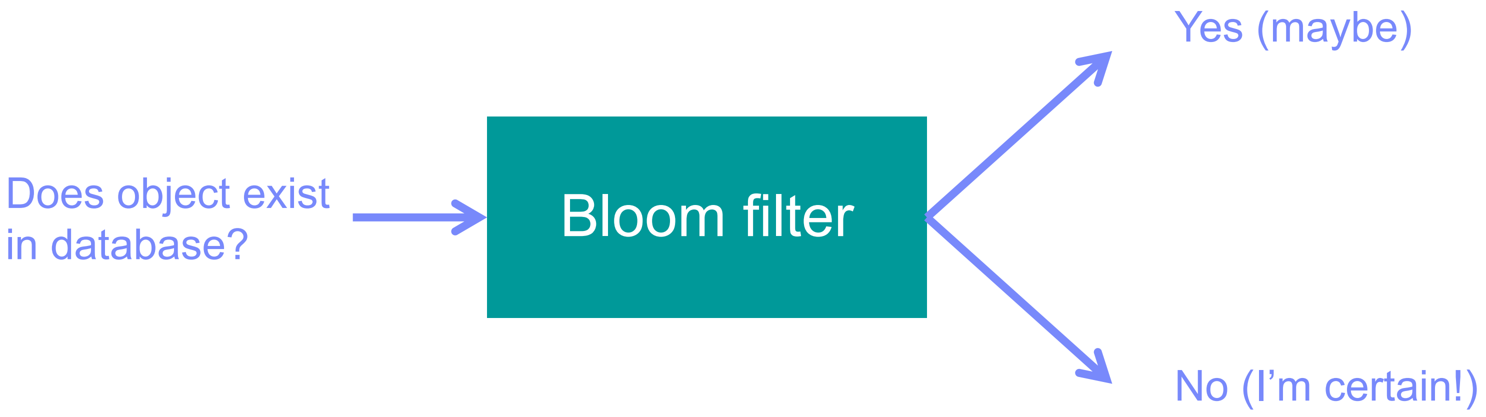
Bloom Filter



Motivation: Index doesn't fit in memory

- Example of a typical database:
  - 64GB memory
  - 2TB flash disk
  - Average key+value (e.g., entry) size: 50B → database needs to store 40 billion keys!
- A pointer needs to locate a key among 40 billion keys
  - Minimum pointer size: 36 bits ~ 4.5 bytes (let's round it to 5 bytes)
    - 2^36 ~= 68 billion
  - Index size = number of keys * byte rounded pointer size ~ 200GB
  - Does not fit in memory
- Therefore, we must use a multi-level index
  - Outer index in memory
  - Inner index on disk
- Minimum time reading a single object: 1 memory access + 2 flash accesses ~ 200us
- What if object doesn't exist in the database?
  - Still 200us!
- Can we do better?

Bloom filters [Bloom 1970]:
Approximate way to determine if object exists



Bloom filter parameters

- An array of m bits (can only be ‘0’ or ‘1’)
  - Array initialized to 0
- k independent **hash functions** $h_1, h_2, \dots h_k$ that return a number between $1, \dots m$

What is a hash function?

- What is a hash function?
  - $h(x) = y$, where y is a uniformly random number
  - In our case, y is a random number between $1, \ldots m$

- If $h(x_1) = h(x_2)$, there is some probability that $x_1 = x_2$
- If $h(x_1)! = h(x_2)$, we are sure that $x_1! = x_2$

Algorithms: check membership and add membership

- To check if x is a member of the bloom filter, check whether $h_1(x), \ldots h_k(x)$ are all set to 1
  - If not, x is definitely not a member
  - If yes, x might be a member
    - There can be false positives!

- To add x, set the positions of $h_1(x), \ldots h_k(x)$ all to 1
  - Some positions might already have been set as 1

How does a bloom filter work? Example

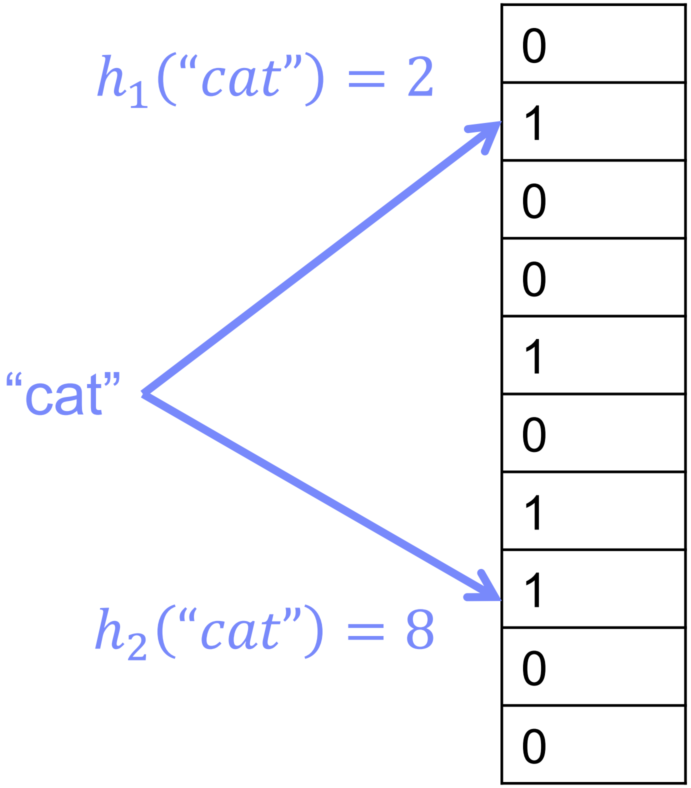
m = 10

k = 2

0
1
0
0
1
0
1
1
0
0

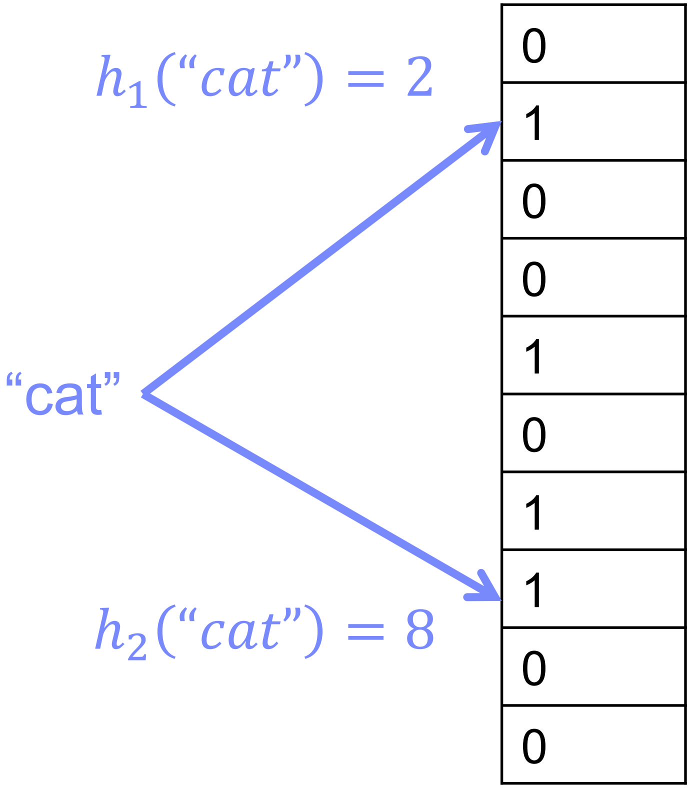
Is cat in DB?

m = 10
k = 2



Is cat in DB? Maybe!

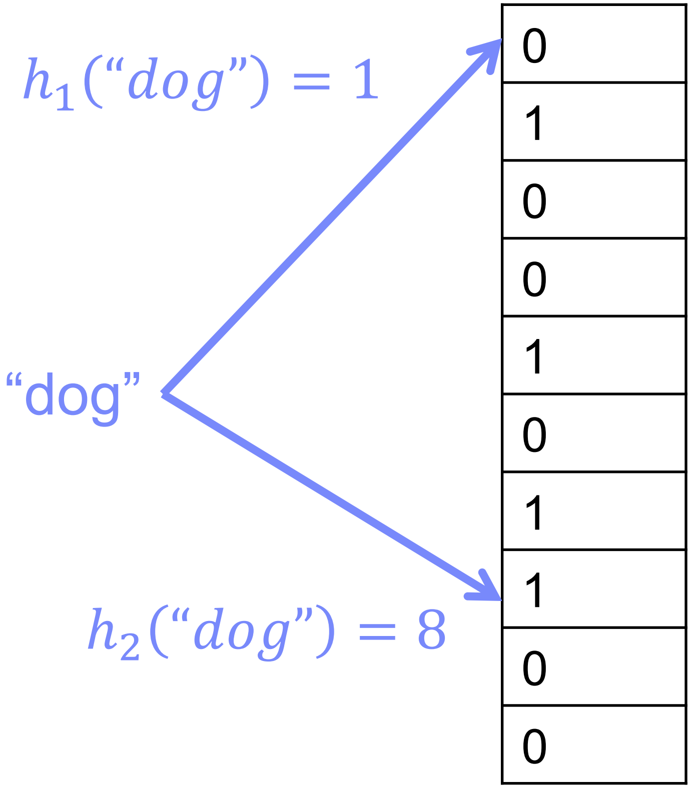
m = 10
k = 2



Cat might exists in DB!

Is dog in DB?

m = 10
k = 2

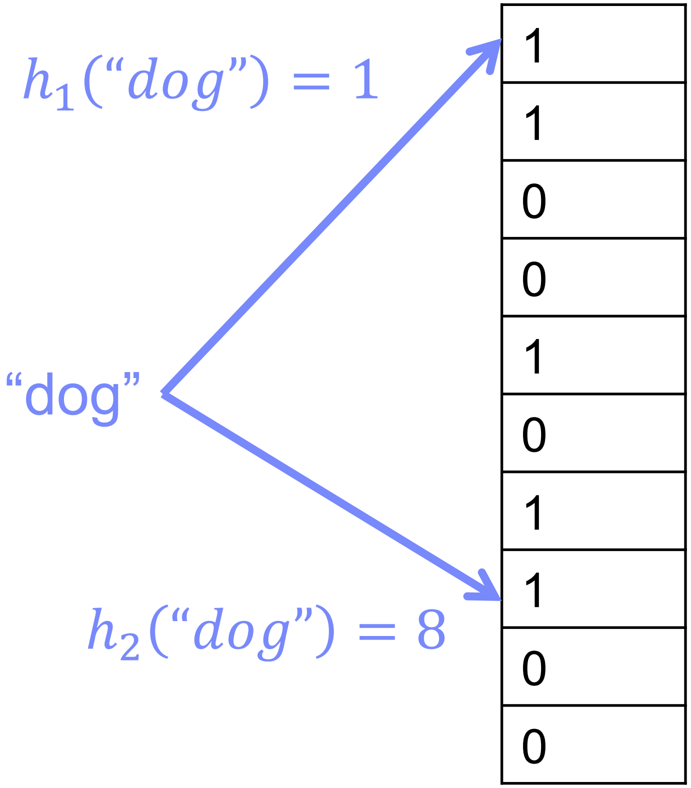


Dog definitely does not exist in DB

→ We don't need to read from disk

Add dog to DB

m = 10
k = 2

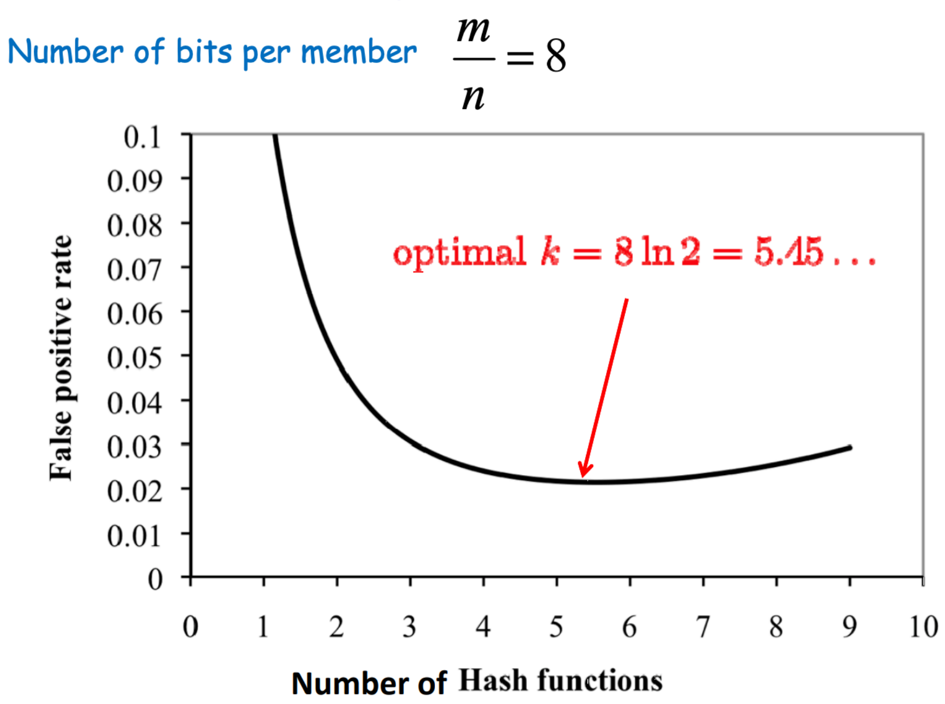


Goal: low false positives

- Define n as the total number of unique objects that might ever be inserted into the database
  - For example, for a bank database that uses account ID as keys, this is the total number of accounts the bank will ever have
- Let's assume $kn < m$

False positive probability (credit: Simon S. Lam)

- The size of k is a trade-off:
  - A higher k increase the number of hash functions that might map to 0
  - But also ”depletes” the available 0 slots in the bloom filter
- Optimal k: $k = \frac{m}{n} ln2$



Bloom filter calculator (https://hur.st/bloomfilter/)

Bloom Filter Calculator

Bloom filters are space-efficient probablistic data structures used to test whether an element is a member of a set.

They're surprisingly simple: take an array of **m** bits, and for up to **n** different elements, either test or set **k** bits using positions chosen using hash functions. If all bits are set, the element *probably* already exists, with a false positive rate of **p**; if any of the bits are not set, the element *certainly* does not exist.

Bloom filters find a wide range of uses, including tracking which articles you've read, speeding up Bitcoin clients, detecting malicious web sites, and improving the performance of caches.

This page will help you choose an optimal size for your filter, or explore how the different parameters interact.

n
: Number of items in the filter (optionally with SI units: k, M, G, T, P, E, Z, Y)
: 4000

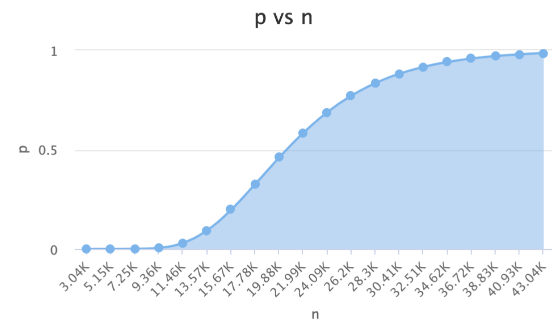
p
: Probability of false positives, fraction between 0 and 1 or a number indicating 1-in-p
: 1.0E-7

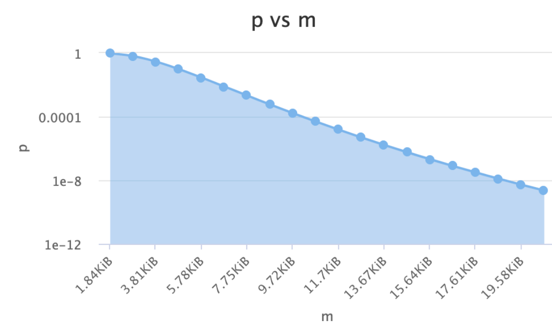
m
: Number of bits in the filter (or a size with KB, KiB, MB, Mb, GiB, etc)

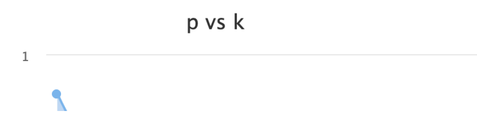
k
: Number of hash functions

Submit

n = 4,000
p = 0.0000001 (1 in 9,994,297)
m = 134,191 (16.38KiB)
k = 23





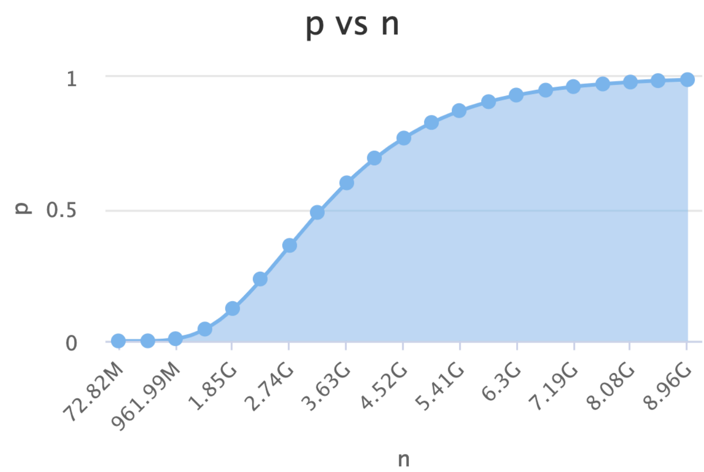


Trade off memory space vs. speed

- Larger bloom filter:
  - Reduces false positives → fewer reads to disk → lower latency, higher throughput
- But…
  - Takes up more space in memory → less space for caching database entries in memory → higher chance of going to disk → higher latency, lower throughput

Example of space vs. speed trade off

- Example: database has 2GB of memory for caching and 100GB of flash
  - Needs to store 1 billion entries (each ~100B)
- Flash access is 100us, memory access is 100ns
- Which bloom filter parameters would you choose?
  1. 600MB bloom filter:
     - Bloom filter false positive rate of 9%
     - 1.4GB of DRAM left → cache hit rate of 90%
  2. 1.1GB bloom filter:
     - Bloom filter false positive rate of 1%
     - 0.9GB of DRAM left → cache hit rate of 70%



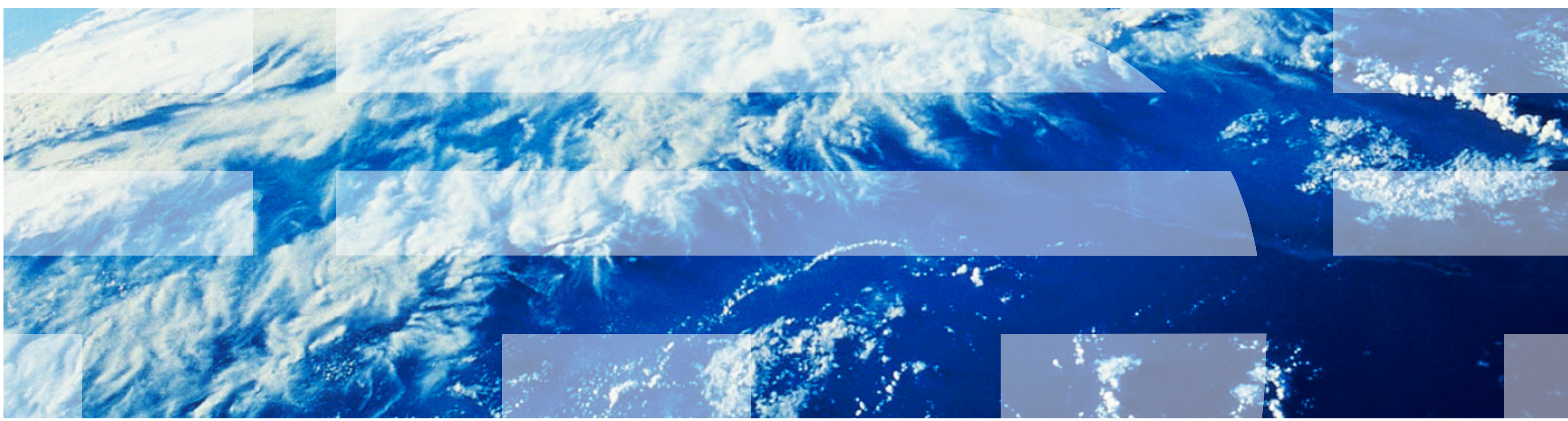
- 60% of requests return object does not exist:
- $\boldsymbol{avg\ latency} = \mathbb{P}(exists) \cdot (\mathbb{P}(cached) \cdot 100ns + \mathbb{P}(not\_cached) \cdot 100\mu s) + \mathbb{P}(doesn't\_exist) \cdot (\mathbb{P}(true\ positive) \cdot 100ns + \mathbb{P}(false\ positive) \cdot 100\mu s)$
- Scenario 1
  - 0.4 * (0.9 * 100ns + 0.1 * 100us) + 0.6 * (0.91 * 100ns + 0.09 * 100us) = **9.49us**
- Scenario 2:
  - **12.64us**

Other issues with bloom filters

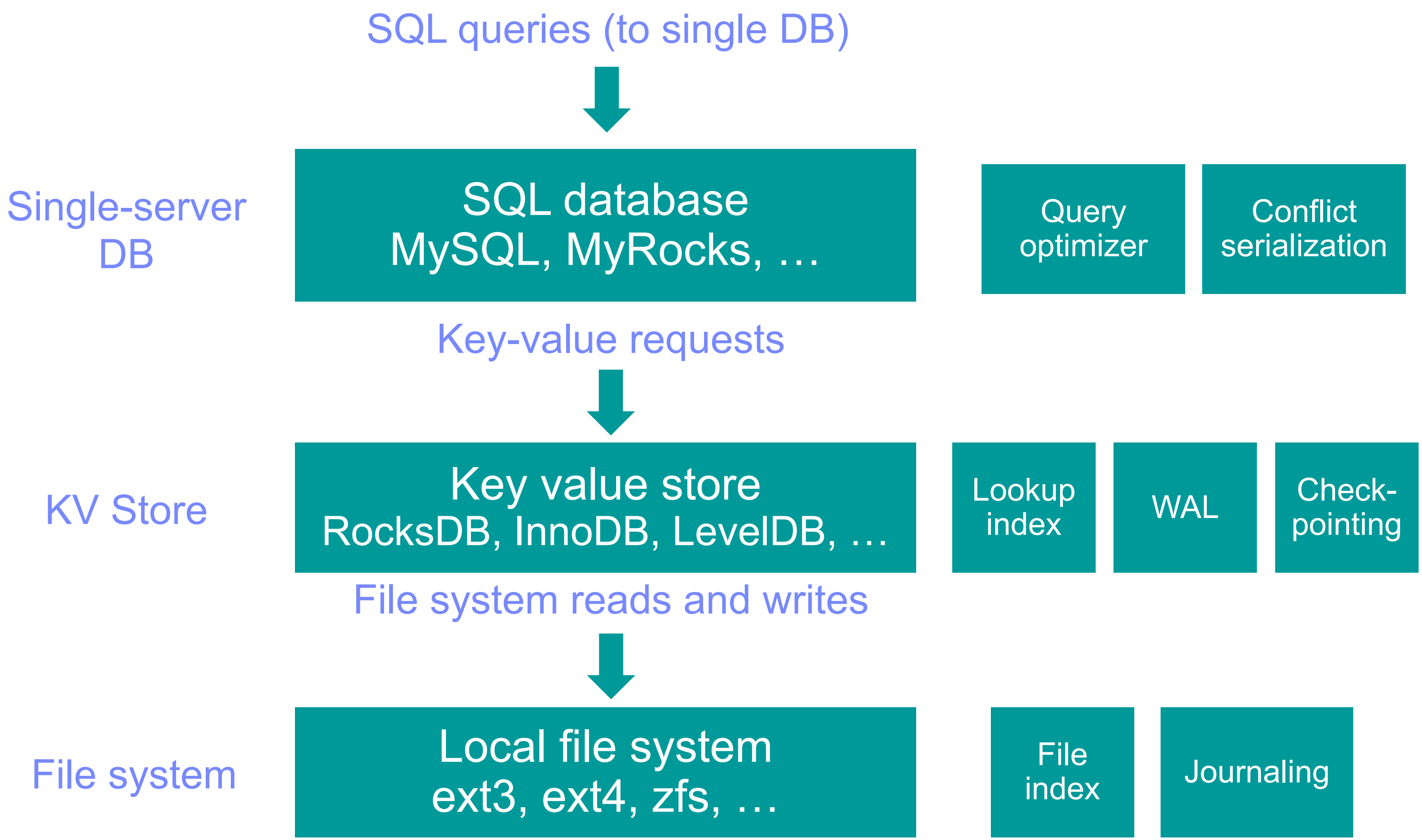
- Can get “depleted” over time
- Need to estimate number of unique entries in advance
- Do not support deletes!
  - Why?

- Improvements: counting bloom filters, cuckoo filters, learned bloom filters, elastic bloom filters… This is a hot research area!

Database Architecture



Modern databases often consist of several layers

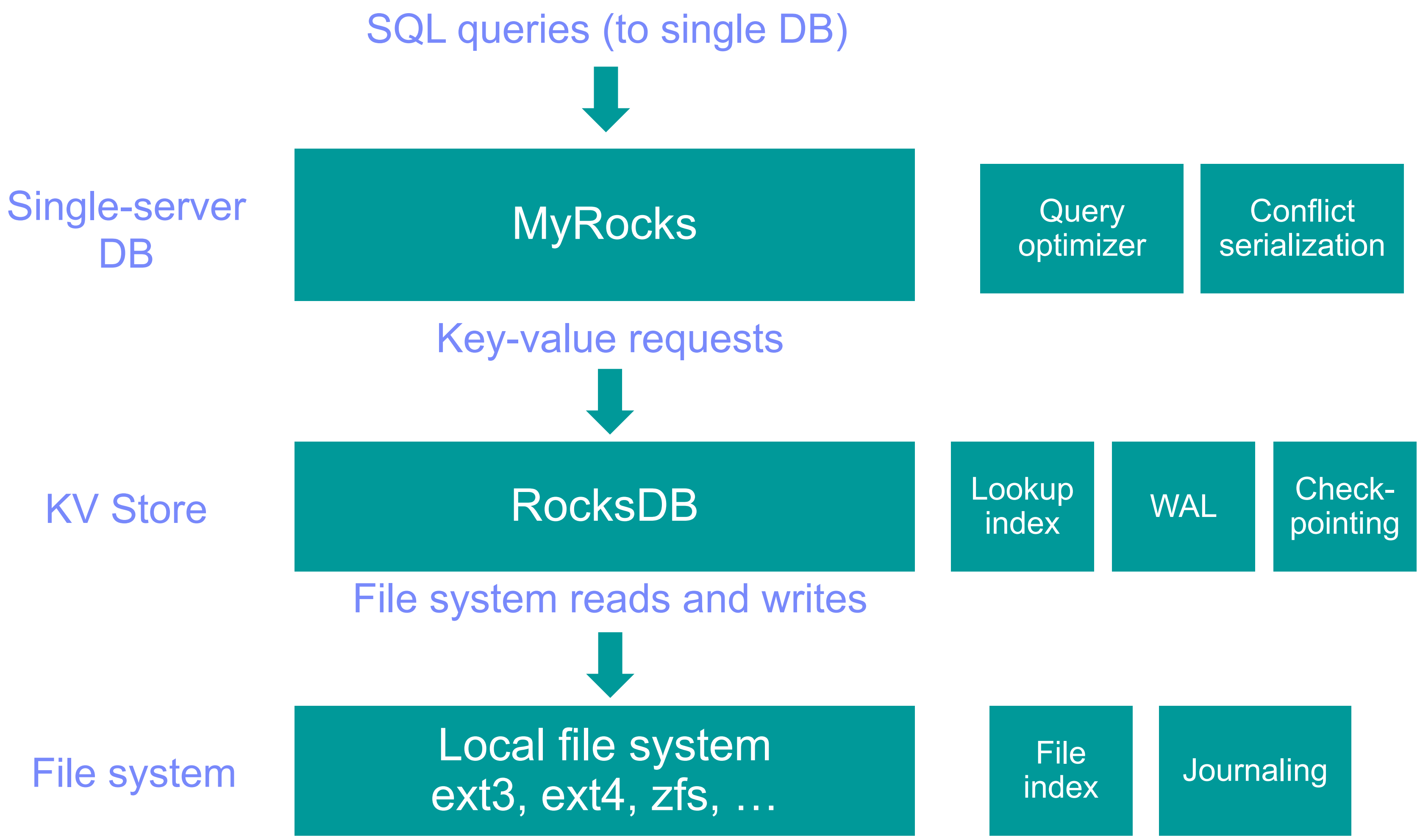


Distributed databases add even another layer

We'll talk more about distributed computer systems later…

Distributed DB	Distributed DB Spanner, CockroachDB, ZippyDB, …	Sharding; Consensus
Single-server DB	SQL database MySQL, MyRocks, …	Query optimizer; Conflict serialization
KV Store	Key value store RocksDB, InnoDB, LevelDB, …	Lookup index; WAL; Check-pointing
File system	Local file system ext3, ext4, zfs, …	File index; Journaling

We’ll focus on one example database: MyRocks + RocksDB



Very brief overview of local file systems

- This is the file system running on the server itself
  - Similar to the file system on your computer!
- Maps physical storage into files, which can be read/written by applications
- Caches some data in memory (file system cached is called *page cache*)
- Logging (similar to WAL) called *file system journal*

- Databases (and other big data systems) often disable many features of file system
  - Don’t care about directories
  - Don’t rely on file system journal for maintaining ACID
  - Often want to manage their own cache

Key-value Stores

- Databases with a really simple interface
  - Do not support SQL
- Get (key)
- Put (key, value)
- Delete (key)
- Sometimes:
  - Update (key, value)
  - Multiget (key1, key2, key3, …)
  - Get_range ([key_i, … key_j])

- Key-value (KV) stores can be used on their own (NoSQL) or can be a foundation for an ACID SQL database

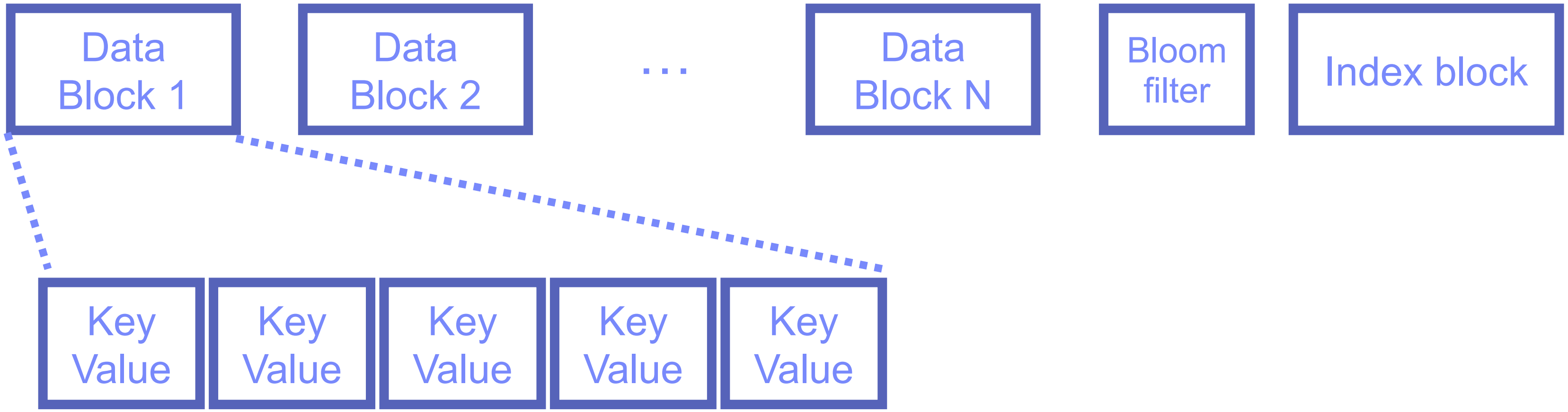
Showcase: RocksDB

- Open source KV store built by Facebook
  - Based on another open source KV store, LevelDB, built by Google
- Optimized for flash
  - Large contiguous writes
  - Generates a relatively small number of writes
- Optimized for range queries
  - Applications often need contiguous range of keys (e.g., get an entire column from a database)

RocksDB components

- Memtable
  - In-memory data structure
  - Stores all incoming writes
    - Why is this a good idea?
  - All writes go to Memtable
  - Small: 64/128MB
- Logfile
  - Write ahead log
  - Sequentially written to
  - Stored persistent in storage (not memory)
- SSTfile
  - Data structure that stores the contents of the database in storage
  - A file that contains a set of **sorted** key-value pairs (keys + values)
  - Organized in **levels**
  - Immutable (i.e., write-only, can never be updated)
    - Why is this a good idea?
  - Sorted data → makes it easier to lookup keys

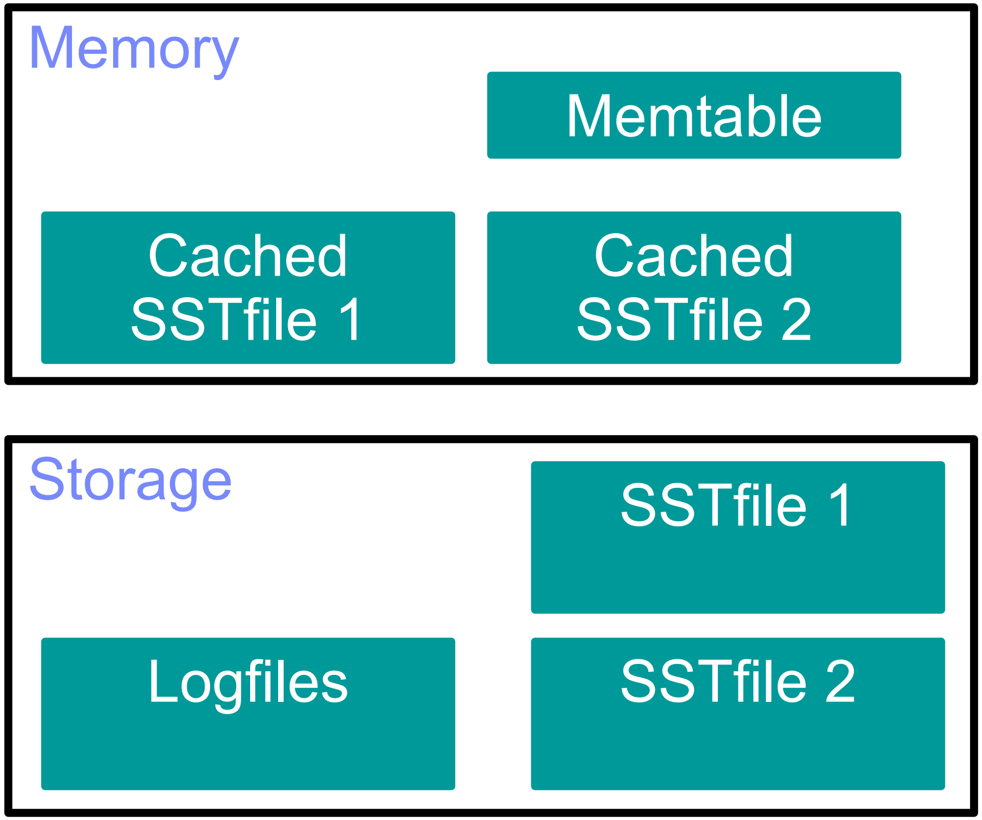
SSTfile structure



SSTfiles and Memtables

- On-disk SSTfiles are always loaded into memory before they are read
- All **writes** go directly to Memtable
- **Reads** check the Memtable first, then the SSTfiles indices
- SSTfile indices and bloom filter are usually cached permanently in DRAM (if they fit)
- Periodically Memtable is **flushed** to disk
- Periodically old on-disk SSTfiles are **merged/compacted** to create new SSTfiles
  - Recall, SSTfiles are immutable, so we need a way to remove stale data (updated/deleted values)
  - Stored in a data structure called **Log-structure Merge Tree (LSM-Tree)**

Simplified architecture



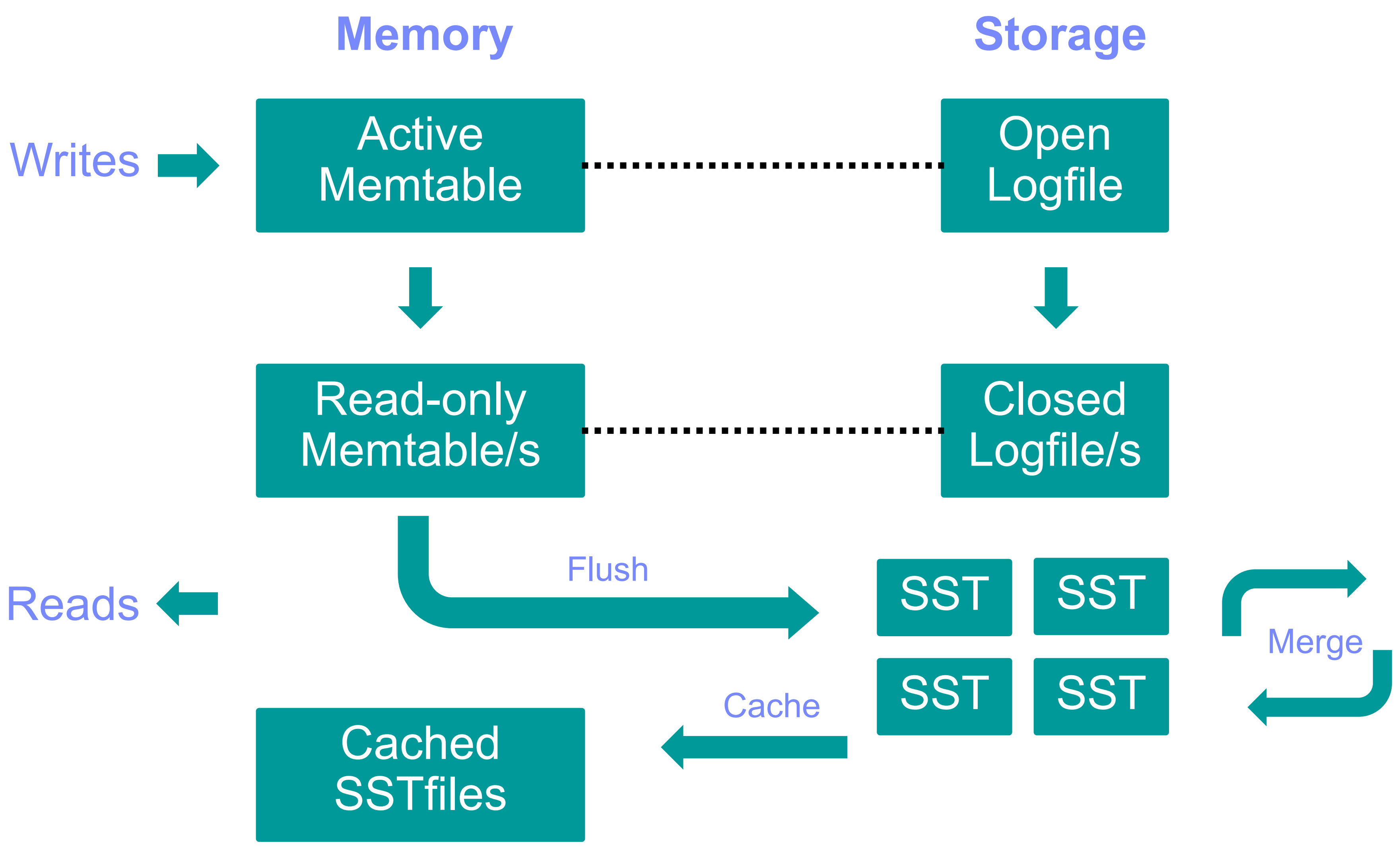
SSTfile index

Key	Offset
Key	Offset
…	…

Simplified SSTfile data

Key	Value	Key	Value	…

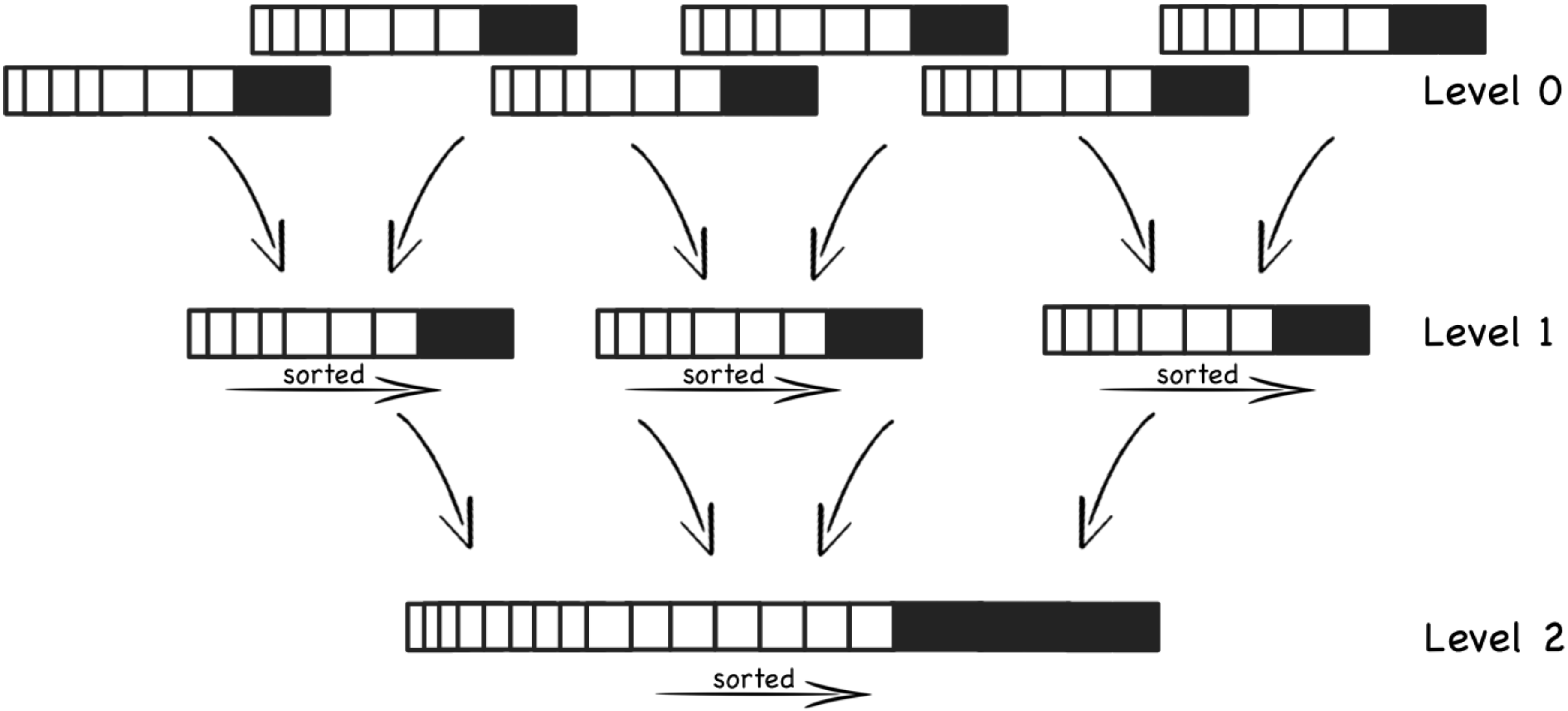
Basic functions



How does RocksDB minimize random writes

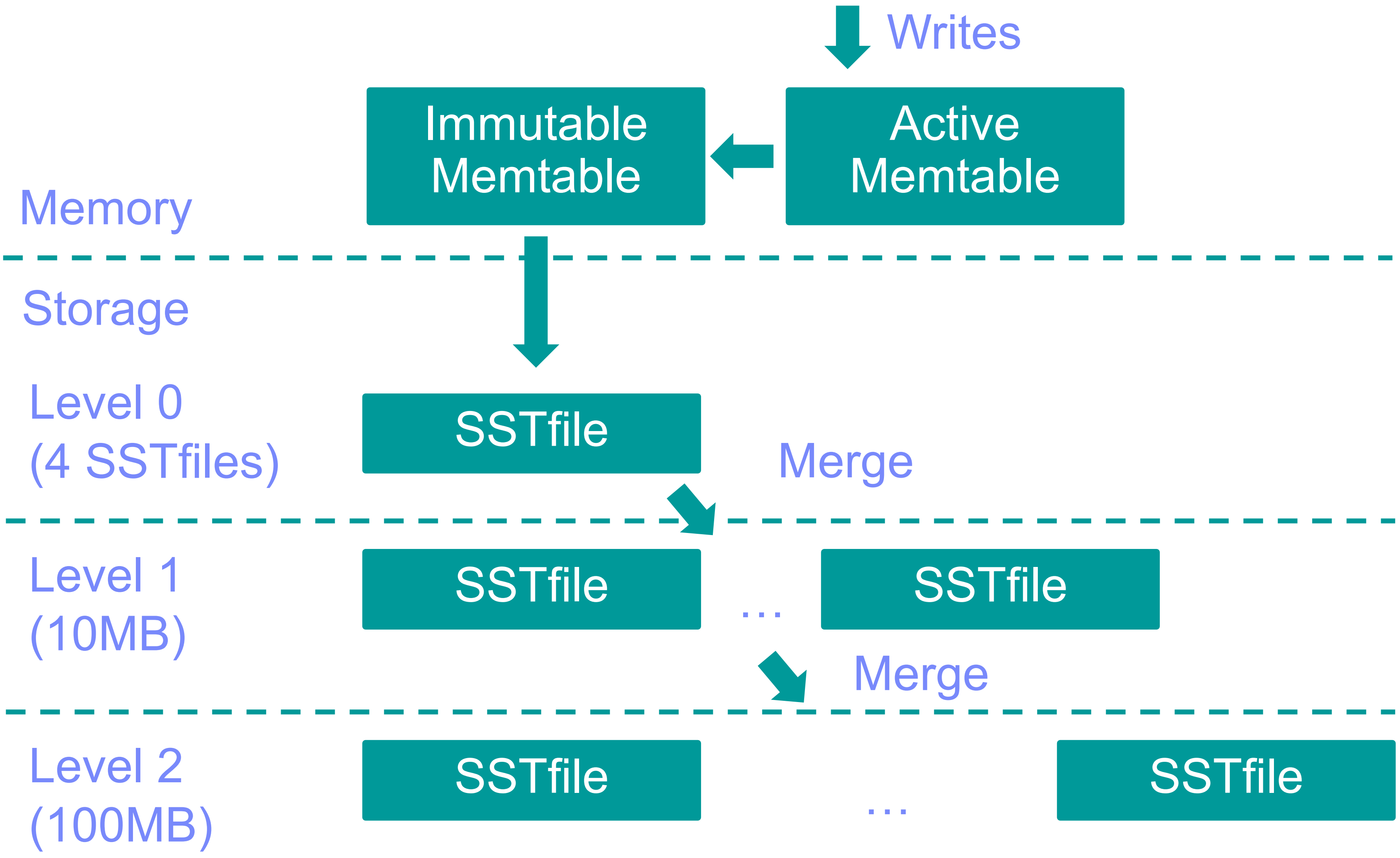
- Data write (insert/update)
  - New data written to memory (Memtable) and to logfile sequentially
  - Memtable fills up → flushed to SSTfile on disk
- Data read
  - Memtable in memory
  - SSTfile indices in memory
    - Use bloom filters to determine existence

Log-structured Merge Tree (LSM-Tree)



Compaction continues creating fewer, larger and larger files

RocksDB LSM-Tree Architecture



LSM-Trees

- Most recently written data is at the top of the tree
  - Newer versions are in a higher level than older version
    - Why? Because older versions get compacted
  - LSM-Tree is searched in order from the highest level
- In RocksDB, highest level is in memory
  - Not sorted
  - Memory has good random write performance (not the case for flash/magnetic disk)
- Data that ends up in the lower levels is not updated frequently

Merging

- Background process periodically merges SSTfiles
  - Parallel computations on different parts of the DB occur simultaneously (using locks)
- Merges SSTfiles from higher level to larger SSTfile in lower level
  - Removes old versions of the same key
  - Removes deleted or overwritten keys
- Each level is 10 times larger than the previous
- In level 0 different SSTfile might contain overlapping key ranges
- In levels 1-n SSTfile key range are not overlapping
  - For example:
    - SSTfile 1: key range: [0, 5]
    - SSTfile 2: key range [6, 202]
    - SSTfile 3: key range [205, 421]
- Every level is 10 times larger than the other
  - Most data sits at the bottom level

Concurrency

- Database maintains a lock table
- Every update acquires a lock beforehand
- Actively check for conflicts

MyRocks (SQL and ACID over RocksDB)

- Implements ACID on top of RocksDB
  - Uses RocksDB locks to implement isolation
- Implements SQL over RocksDB API
  - Translates rows/columns to gets/puts/multigets